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Findings of the WMT 2017 Biomedical Translation Shared Task

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Abstract

Automatic translation of documents is an important task in many domains, including the biological and clinical domains. The second edition of the Biomedical Translation task in the Conference of Machine Translation focused on the automatic translation of biomedical-related documents between English and various European languages. This year, we addressed ten languages: Czech, German, English, French, Hungarian, Polish, Portuguese, Spanish, Romanian and Swedish. Test data included both scientific publications (from the Scielo and EDP Sciences databases) and health-related news (from the Cochrane and UK National Health Service web sites). Seven teams participated in the task, submitting a total of 82 runs. Herein we describe the datasets, participating systems and results of both the automatic and manual evaluation of the translations.

1 Introduction

Automatic translation of texts allows readers to gain access to information present in documents written in a language in which the reader is not fluent. We identify two main use cases of machine translation (MT) in the biomedical domain: (a) making health information available to health professionals and the general public in their own language; and (b) assisting health professionals and researchers in writing reports of their research in English. In addition, it creates an opportunity for natural language processing (NLP) tools to be applied to domain-specific texts in languages for which few domain-relevant tools are available; i.e., the texts can be translated into a language for which there are more resources.

The second edition of the Biomedical Translation Task in the Conference for Machine Translation (WMT)[1] builds on the first edition (Bojar et al., 2016) by offering seven additional language pairs and new datasets. This year, we expanded to a total of ten languages in the biomedical task, namely, Czech (cs), German (de), English (en), French (fr), Hungarian (hu), Polish (pl), Portuguese (pt), Spanish (es), Romanian (ro) and Swedish (sv). Test sets included scientific publications from the Scielo and EDP Sciences databases and health-related news from Cochrane and the UK National Health Service (NHS).

Participants were challenged to build systems to enable translation from English to all other lan-

[1] http://www.statmt.org/wmt17/biomedical-translation-task.html

guages, as well as from French, Spanish and Portuguese to English. We provided both training and development data but the teams were allowed to use additional in-domain or out-of-domain training data. After release of the test sets, the participants had 10 days to submit results (automatic translations) for any of the datasets and languages. We allowed up to three runs per team for each language pair and dataset.

We evaluated the submission both automatically and manually. In this work, we report details on the challenge, datasets, participating teams, the results they obtained and the quality of the automatic translations.

2 Training and test sets

We released test sets from four sources, namely, Scielo, EDP, Cochrane and NHS, as presented in Table 1. For training and development data, we referred participants to various biomedical corpora: (a) Biomedical Translation Corpora Repository[2], which includes titles from MEDLINE® and the Scielo corpus (Neves et al., 2016); (b) UFAL corpus[3], which includes EMEA and PatTR Medical, among others; (c) development data from the Khresmoi project[4]. We provide details of the test datasets below.

Scielo. Similar to last year, this dataset consisted of titles and abstracts from scientific publications retrieved from the Scielo database[5] and addressed the following language pairs: es/en, en/es, pt/en and en/pt. There were not enough articles indexed in 2017 with French titles or abstracts, so we relied on another source for en/fr and fr/en language pairs (namely, EDP as described below). Similar to last year, we crawled the Scielo site for publications containing both titles and abstracts in both English/Spanish or English/Portuguese language pairs. We considered only articles published in 2017 until that point (April/2017). We tokenized the documents using Apache OpeNLP[6] (with specific models for each language). The test set dataset was automatically created by aligning the GMA tool[7]. We manually checked the alignment of a sample and confirmed that around 88% of the sentences were correctly aligned.

EDP. Title and abstracts of scientific publications were collected from the open access publisher EDP Sciences[8] on March 15, 2017. The corpus comprises a selection of titles and abstracts of articles published in five journals in the fields of *Health* and *Life & Environmental Sciences*. The articles were originally written in French but the journals also publish the titles and abstracts in English, using a translation provided by the authors. The dataset was pre-processed for sentence segmentation using the Stanford CoreNLP toolkit[9] and aligned using YASA[10]. Manual evaluation conducted on a sample set suggests that 94% of the sentences are correctly aligned, with about 20% of the sentence pairs exhibiting additional content in one of the languages.

Cochrane and NHS. The test data was produced during the course of the KConnect[11] and HimL[12] projects. The test data contains health-related documents from Cochrane and NHS that were manually translated by experts from English to eight languages: cs, de, fr, hu, pl, ro, es and sv.

3 Participating teams and systems

We received submissions from seven teams, as summarized in Table 2. The teams came from a total of five countries (Germany, Japan, Poland, UK and USA) and from three continents. They include both research institutions and a company. An overview of the teams and their systems is provided below.

Hunter (Hunter College, City University of New York). The system from the Hunter College is based on Moses EMS, SRI-LM, GIZA++. For the translation model, they generate word alignments using GIZA++ and mGIZA. For the language model, they relied on an interpolation of models that includes 6-grams with Kneser-Ney smoothing. Different corpora were used for the various languages to which they submitted runs.

[2] https://github.com/biomedical-translation-corpora/wmt-task
[3] https://ufal.mff.cuni.cz/ufal_medical_corpus
[4] https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-2122
[5] http://www.scielo.org
[6] https://opennlp.apache.org/
[7] http://nlp.cs.nyu.edu/GMA/
[8] http://www.edpsciences.org
[9] https://stanfordnlp.github.io/CoreNLP/
[10] http://rali.iro.umontreal.ca/rali/?q=en/yasa
[11] http://k-connect.org
[12] http://www.himl.eu/

Datasets	en/cs	en/de	fr/en	en/hu	pt/en	es/en	en/fr	en/pl	en/pt	en/es	en/ro	en/sv
Scielo					189/1897	158/1180			188/1806	158/1082		
EDP			85/699				84/750					
Cochrane	25/467	25/467	25/467	25/467		25/467	25/467	25/467		25/467	25/467	25/467
NHS	25/1044	25/1044	25/1044	25/1044		25/1044	25/1044	25/1044		25/1044	25/1044	25/1044

Table 1: Overview of the test sets. We present the number of documents and sentences in each dataset.

Team ID	Institution
Hunter	Hunter College, City University of New York
kyoto	Kyoto University
Lilt	Lilt Inc.
LMU	Ludwig Maximilian University of Munich
PJIIT	Polish-Japanese Academy of Information Technology
uedin-nmt	University of Edinburgh
UHH	University of Hamburg

Table 2: Overview of the participating teams.

The system was tuned using the WMT16 test sets (in the case of French and English) and on the HimL test sets for Cochrane and NHS. For training data, the team relied on a variety of corpora, depending on the language pair, which included MEDLINE, Europarl, Scielo, News Commentary, UFAL, EMEA, Cordis, among others.

kyoto (Kyoto University). The system from the team from Kyoto University is based on two previous papers (Cromieres et al., 2016; Cromieres, 2016). The participants describe it as a classic neural machine translation (NMT) system, however, we do not have further information regarding the datasets that have been used to train and tune the system for the WMT challenge.

Lilt (Lilt Inc.). The system from the Lilt Inc.[13] uses an in-house implementation of a sequence-to-sequence model with Bahdanau-style attention. The final submissions are ensembles between models fine-tuned on different parts of the available data.

LMU (Ludwig Maximilian University of Munich). LMU Munich has participated with an en2de NMT system (Huck and Fraser, 2017). A distinctive feature of their system is a linguistically informed, cascaded target word segmentation approach. Fine-tuning for the domain of health texts was done using in-domain sections of the UFAL Medical Corpus v.1.0 as a training corpus. The learning rate was set to 0.00001, initialized with a pre-trained model, and optimized using only the in-domain medical data. The HimL tuning sets were used for validation, and they tested separately on the Cochrane and NHS24 parts of the HimL devtest set.

PJIIT (Polish-Japanese Academy of Information Technology). PJIIT developed a translation model training, created adaptations of training settings for each language pair, and implemented byte pair encoding (BPE) (subword units) in their systems (Wolk and Marasek, 2017). Only the official parallel text corpora and monolingual models for the challenge evaluation campaign were used to train language models, and to develop, tune, and test their system. PJIIT explored the use of domain adaptation techniques, symmetrized word alignment models, the unsupervised transliteration models and the KenLM language modeling tool.

uedin-nmt (University of Edinburgh). The systems from the University of Edinburgh used a NMT trained with Nematus, an attentional encoder-decoder (Sennrich et al., 2017). Their setup follows the one from last year. This team again built BPE-based models with parallel and back-translated monolingual training data. New approaches this year included the use of deep architectures, layer normalization, and more compact models due to weight-tying and improvements in BPE segmentations.

UHH (University of Hamburg). All SMT models were developed using the Moses phrase-based MT toolkit and the Experiment Management System (Duma and Menzel, 2017). The preprocessing of the data consisted of tokenization, cleaning (6-80), lowercasing and normalizing punctuation. The tuning and the test sets were derived from WMT 2016 and WMT 2017. The SRILM toolkit and Kneser-Ney discounting were used to estimate

[13] `https://lilt.com/`

5-gram language models (LM). For word alignment, GIZA++ with the default grow-diag-final-and alignment symmetrization method was used. Tuning of the SMT systems was performed with MERT. Commoncrawl and Wikipedia were used as general domain data for all language pairs except for EN/PT, where no Commoncrawl data was provided by WMT. As for the in-domain corpora, EMEA was used for all language pairs and Muchmore, ECDC, Pattr and Pubmed (all from UFAL Medical Corpus2) for the language pairs where data was available. The system made use of the training data provided by the previous Biomedical task from 2016. The corpora corresponding to the general domain were concatenated into a single data source and the same procedure was applied for the in-domain corpora. This team investigated performing data selection for MT via Paragraph Vector and a Feed Forward Neural Network Classifier. Continuous distributed vector representations of the sentences were used as features for the classifier.

4 Evaluation

In this section, we present an overview of the submissions to the Biomedical Task and results in terms of both automatic and manual evaluation.

4.1 Submissions

An overview of the submissions is shown is Table 3. The participating teams submitted a total of 82 runs. No submissions were received for Swedish (en/sv) and Hungarian (en/hu).

4.2 Baselines

We provided baseline results only for the EDP and Scielo datasets, however, not for the other languages included in the Cochrane and NHS datasets.

baseline. For the Scielo and EDP datasets, we compared the participants' results to our baseline system, which used the same approach as applied in last year's challenge (Bojar et al., 2016) for the evaluation of the Scielo dataset (Neves et al., 2016). The statistical machine translation (SMT) system used for the baseline was Moses (Koehn et al., 2007) with default settings. For es2en, en2es, fr2en, en2fr, pt2en and en2pt, the baseline system was trained as described in (Neves et al., 2016).

LIMSI baseline. For additional comparison, we also provided the results of an en2fr Moses-based system prepared by Ive et al. for their participation in the WMT16 biomedical track, which reflects the state of the art for this language pair (Ive et al., 2016a). The system uses in-domain parallel data provided for the biomedical task in 2016, as well as additional in-domain data[14] and out-of-domain data. However, we did not perform SOUL re-scoring.

4.3 Automatic evaluation

In this section, we provide the results for the automatic evaluation and rank the various systems based on those results. For the automatic evaluation, we computed BLEU scores at the sentence level using the multi-bleu and tokenization scripts as provided by Moses (`tokenizer` and `truecase`). For all datasets and language pairs, we compare the automatic translations to the reference one, as provided by each dataset.

Results for the Scielo dataset are presented in Table 4. All three runs from the UHH team, for all four language pairs, obtained a much higher BLEU score than our baseline. However, this is not surprising given the simplicity of the methods used in the baseline system.

The BLEU scores for the EDP dataset are presented in Table 5. While all system runs score above the baseline, only the Kyoto system outperforms the stronger baseline for en2fr. We rank the various submissions as follows:

- fr2en: Hunter (runs 1,2) < baseline < UHH (runs 1,2) < UHH (run 3) < kyoto (run 1).
- en2fr: baseline < Hunter (runs 1,2) < UHH (runs 1,2,3) < LIMSI baseline < kyoto (run 1) < kyoto (run 2).

The BLEU scores for the Cochrane dataset are presented in Table 6. The scores range from as low as 12.45 (for Polish) to as high as 48.99 (for Spanish). All scores were particularly high for Spanish (close to 50), but rather low for Polish and Czech (all below 30). While the BLEU value did not vary much for French (all around 30), these went from a range of 14 to 41 for Romanian. We rank the various submissions for each language as below:

[14] Cochrane translation corpus available at http://www.translatecochrane.fr/corpus/ (Ive et al., 2016b)

Teams	en/cs	en/de	fr/en	pt/en	es/en	en/fr	en/pl	en/pt	en/es	en/ro
Hunter		CN	E2			C2NE2	CN			CN
kyoto			E			E2				
lilt		C2N2								
LMU		CN								
PJIIT	CN	CN					C3N3			CN
uedin-nmt	CN	CN					C2N2			C2N2
UHH		C3N3	E3	S3	S3	C3N3E3		S3	C3N3S3	

Table 3: Overview of submissions for each language pair and dataset: [E]DP, [S]cielo, [C]ochrane and [N]HS. The number next to the letter indicates the number of runs that the team submitted for the corresponding dataset.

Runs	pt/en	es/en	en/pt	en/es
baseline	36.35	31.50	30.52	27.31
UHH run1	43.84	37.14	39.14	36.08
UHH run2	43.93	37.47	39.38	35.93
UHH run3	43.88*	37.49*	39.21*	36.23*

Table 4: Results for the Scielo dataset. * indicates the primary run as identified by the participants.

Runs	fr/en	en/fr
baseline	17.47	12.32
LIMSI baseline	-	24.05
Hunter run1	15.10*	17.50*
Hunter run2	15.18	17.21
kyoto run1	25.21*	25.52
kyoto run2	-	27.04*
UHH run1	22.64	22.43
UHH run2	22.37	22.25
UHH run3	23.41*	22.79*

Table 5: Results for the EDP dataset. * indicates the primary run as declared by the participants.

- cs: PJIIT (run 1) < uedin-nmt (run 1).
- de: UHH (runs 1,2,3) < Hunter (run 1) < PIIJT (run 1) < lilt (run 1,2) < LMU < uedin-nmt (run 1).
- fr: Hunter (runs 1,2) < UHH (runs 1,2,3).
- pl: PIIJT (run 2) < Hunter (run 1) < PIIJT (runs 1,3) < uedin-nmt (run 2) < uedin-nmt (run 1).
- ro: Hunter (run 1) < PIIJT (run 1) < uedin-nmt (run 2) < uedin-nmt (run 1).

Finally, the BLEU scores for the NHS dataset are presented in Table 7. The scores range from as low as 10.56 (for Romanian, the lowest score across all datasets and languages) to as high as 41.22 (for Spanish). All scores were particularly high for Spanish (around 40), but rather low for Polish, Czech and Romanian (all below 30). We rank the various submissions for each language as shown below:

- cs: PJIIT (run 1) < uedin-nmt (run 1).
- de: UHH (runs 1,2,3) < Hunter (run 1) < PIIJT (run 1) < lilt (run 1,2) < LMU < uedin-nmt (run 1).
- fr: Hunter (run 1) < UHH (runs 1,2) < UHH (run 3).
- pl: PIIJT (run 2) < Hunter (run 1), PIIJT (runs 1,3) < uedin-nmt (run 2) < uedin-nmt (run 1).
- ro: Hunter (run 1) < PIIJT (run 1) < uedin-nmt (run 2) < uedin-nmt (run 1).

The BLEU values were generally lower for NHS than the ones obtained for the same teams for the Cochrane datasets. However, the rankings of systems and runs are nearly the same for the Cochrane and NHS datasets. The only exceptions were in French, where run 3 from UHH was higher than the others from the team, and for Polish, where the scores for Hunter and PIIJT (runs 1,3) were nearly the same.

4.4 Manual evaluation

We required teams to identify a primary run for each language pair, in the case that they submitted more than one run. These are the runs for which we performed manual evaluation. The following runs were considered to be primary: Hunter (run1), kyoto (run2 for en/fr, run1 for fr/en), lilt (run1), LMU (run1), PJIIT (run3 for pl, otherwise, run1), uedin-nmt (run1), UHH (run3).

We computed pairwise combinations of translations either between two automated systems, or one automated system and the reference translation. We compared all systems (primary) to the reference translation, as well as to each other. We ran manual validation for all target languages, except for Czech (cs), for which we could not find

Cochrane	cs	de	fr	pl	es	ro
Hunter run1	-	24.72*	30.75*	17.16*	-	14.74*
Hunter run2	-	-	30.76	-	-	-
lilt run1	-	34.91*	-	-	-	-
lilt run2	-	33.97	-	-	-	-
LMU	-	36.44*	-	-	-	-
PJIIT run1	19.96*	25.13*	-	18.86	-	24.91*
PJIIT run2	-	-	-	12.45	-	-
PJIIT run3	-	-	-	18.88*	-	-
uedin-nmt run1	28.54*	37.11*	-	29.04*	-	41.18*
uedin-nmt run2	-	-	-	27.69	-	38.89
UHH run1	-	22.03	32.46	-	48.99	-
UHH run2	-	22.37	32.59	-	48.45	-
UHH run3	-	22.63*	33.16*	-	48.70*	-

Table 6: Results for the Cochrane dataset. * indicates the primary run as informed by the participants.

NHS	cs	de	fr	pl	es	ro
Hunter	-	20.45*	22.99*	14.09*	-	10.56*
lilt run1	-	27.57*	-	-	-	-
lilt run2	-	26.79	-	-	-	-
LMU	-	29.46*	-	-	-	-
PJIIT run1	15.93*	21.88*	-	14.32	-	18.10*
PJIIT run2	-	-	-	10.75	-	-
PJIIT run3	-	-	-	14.34*	-	-
uedin-nmt run1	22.79*	33.06*	-	23.15*	-	29.32*
uedin-nmt run2	-	-	-	19.87	-	27.32
UHH run1	-	18.71	31.79	-	40.97	-
UHH run2	-	19.80	31.89	-	41.20	-
UHH run3	-	19.66*	33.36*	-	41.22*	-

Table 7: Results for the NHS dataset. * indicates the primary run as informed by the participants.

available native speakers. The human validators were native speakers of the languages and were either members of the participating teams or colleagues from the research community.

The validation task was carried out using the Appraise tool[15] (Federmann, 2010). For each pairwise comparison, we validated a total of 100 randomly-chosen sentence pairs. The validation consisted of reading the two sentences (A and B), i.e., translations from two systems or from the reference, and choosing one of the options below:

- A<B: when the quality of translation B was higher than A.
- A=B: when both translation had similar quality.
- A>B: when the quality of translation A was higher than B.
- Flag error: when the translations did not seem to be derived from the same input sentence. This is usually derived from error in the corpus alignment (for the Scielo and EDP datasets).

[15]https://github.com/cfedermann/Appraise

The manual validation for the Scielo datasets is presented in Table 8, for the comparison of the only participating team (UHH) to the reference translation. For en2es, the automatic translation scored lower than the reference one in 53 out of 100 pairs, but could still beat the reference translation in 23 pairs. For en2pt, the automatic translation was better only on 13 sentences pairs, while they could achieve similar quality to the reference translation on 31 cases. In the case of translations from Spanish or Portuguese to English, the reference scored better than the UHH around the same proportion, while the latter could only beat the reference in very few cases.

We present the results for the manual evaluation of the EDP corpus in Table 9. Based on the number of times that a translation was validated as being better than another, we ranked the systems for each language as listed below:

- en2fr: Hunter $<$ UHH $<$ kyoto = reference
- fr2en: Hunter $<$ UHH $<$ kyoto $<$ reference

Results for manual validation of the Cochrane dataset are presented in Table 10. We rank the various system as shown below:

Datasets	Languages	Runs (A vs. B)	Total	A<B	A=B	A>B
Scielo	en2es	UHH vs. reference	100	53	24	23
	en2pt	UHH vs. reference	100	46	31	13
	es2en	UHH vs. reference	100	59	11	7
	pt2en	UHH vs. reference	100	50	20	10

Table 8: Results for the manual validation for the Scielo datasets.

Datasets	Languages	Runs (A vs. B)	Total	A<B	A=B	A>B
EDP	en2fr	UHH vs. reference	100	87	4	3
		UHH vs. Hunter	100	7	46	42
		UHH vs. kyoto	100	64	21	10
		reference vs. Hunter	100	0	2	93
		reference vs. kyoto	100	28	30	35
		Hunter vs. kyoto	100	82	10	3
	fr2en	UHH vs. reference	100	72	9	5
		UHH vs. Hunter	100	10	5	79
		UHH vs. kyoto	100	62	7	25
		reference vs. Hunter	100	2	4	79
		reference vs. kyoto	100	25	9	48
		Hunter vs. kyoto	100	81	9	3

Table 9: Results for the manual validation for the EDP datasets.

- de: UHH < Hunter = PJIIT < Lilt < LMU < uedin-nmt = reference
- fr: UHH < Hunter < reference
- pl: Hunter = PIIJT < uedin < reference
- es: UHH < reference
- ro: Hunter < PIIJT < uedin < reference

Results for manual validation of the NHS dataset are presented in Table 11. We rank the various system as shown below:

- de: Hunter = UHH < PIIJT < Lilt < LMU = uedin-nmt < reference
- fr: UHH < Hunter < reference
- pl: Hunter < PIIJT < uedin < reference
- es: UHH < reference
- ro: Hunter < PIIJT < uedin < reference

For the Polish language in the NHS dataset, the validator skipped too many sentences (68 out of 100) to enable a comparison between Hunter and PIIJT. However, we ranked the PIIJT system higher than Hunter given that the former scored 21 times better that the latter (in contrast to 7). However, there is inadequate data to support assigning a clear difference between the two systems. Indeed, both systems have similar quality for this language in the Cochrane dataset.

5 Discussion

In this section we discuss, for each target language, some insights from the automatic validation, the quality of the translations, as well as future work that we plan to implement in the next edition of the challenges.

5.1 Performance of the systems

The results obtained by the teams show interesting point of discussion regarding the impact of methods and amount of training data. The highest BLEU score (48.99) of all runs was obtained by the UHH system for en2es (Cochrane test set). The same team also scored high (above 40) for the NHS en2es dataset and for the Scielo pt2en dataset. The only other team that obtained BLEU scores in the same range (above 40) was uedin-nmt for the Cochrane en2ro test set.

No automatic system was able to outperform or match the reference translations on manual evaluation; hence the automated systems all still have room for improvement. Interestingly, it can be noted that the best performing system on the EDP en2fr dataset (Kyoto) compared very favorably to the reference and was found to be better or equal to the reference in 62% of the manually evaluated sentences. In general, the kyoto and uedin-nmt systems seemed to consistently outperform other competitors.

Regarding comparison of results to the ones obtained in the last year's edition of the challenge, we can only draw conclusions for the Scielo dataset. The only participating team (UHH)

Datasets	Languages	Runs (A vs. B)	Total	A<B	A=B	A>B
Cochrane	de	Hunter vs. reference	100	83	12	5
		Hunter vs. Lilt	100	68	20	12
		Hunter vs. LMU	100	73	20	6
		Hunter vs. PJIIT	100	33	41	26
		Hunter vs. uedin-nmt	100	85	12	3
		Hunter vs. UHH	100	28	30	42
		reference vs. Lilt	100	19	22	59
		reference vs. LMU	100	17	32	51
		reference vs. PJIIT	100	2	8	90
		reference vs. uedin-nmt	100	31	29	40
		reference vs. UHH	100	1	6	93
		Lilt vs. LMU	100	50	24	23
		Lilt vs. PJIIT	100	15	19	66
		Lilt vs. uedin-nmt	100	63	22	14
		Lilt vs. UHH	100	11	8	81
		LMU vs. PJIIT	100	7	9	82
		LMU vs. uedin-nmt	100	31	50	19
		LMU vs. UHH	100	3	10	82
		PJIIT vs. uedin-nmt	100	64	22	14
		PJIIT vs. UHH	100	22	44	34
		uedin-nmt vs. UHH	100	8	5	87
	fr	UHH vs. reference	100	83	8	8
		UHH vs. Hunter	100	40	51	8
		reference vs. Hunter	100	11	10	79
	pl	Hunter vs. PJIIT	100	48	7	43
		Hunter vs. reference	100	88	8	4
		Hunter vs. uedin-nmt	100	84	0	16
		PJIIT vs. reference	100	86	11	3
		PJIIT vs. uedin-nmt	100	80	4	16
		reference vs. uedin-nmt	100	15	34	51
	es	reference vs. UHH	100	4	29	67
	ro	Hunter vs. PJIIT	100	74	20	6
		Hunter vs. reference	100	96	3	1
		Hunter vs. uedin-nmt	100	87	8	5
		PJIIT vs. reference	100	91	6	3
		PJIIT vs. uedin-nmt	100	59	21	20
		reference vs. uedin-nmt	100	4	32	64

Table 10: Results for the manual validation for the Cochrane datasets.

Datasets	Languages	Runs (A vs. B)	Total	A<B	A=B	A>B
NHS	de	Hunter vs. reference	100	91	9	0
		Hunter vs. Lilt	100	43	29	28
		Hunter vs. LMU	100	68	12	17
		Hunter vs. PJIIT	100	40	28	32
		Hunter vs. uedin-nmt	100	70	18	12
		Hunter vs. UHH	100	30	36	34
		reference vs. Lilt	100	2	35	63
		reference vs. LMU	100	4	30	62
		reference vs. PJIIT	100	1	24	74
		reference vs. uedin-nmt	100	5	45	46
		reference vs. UHH	100	2	18	79
		Lilt vs. LMU	100	33	44	19
		Lilt vs. PJIIT	100	30	24	46
		Lilt vs. uedin-nmt	100	66	23	11
		Lilt vs. UHH	100	25	28	47
		LMU vs. PJIIT	100	18	22	56
		LMU vs. uedin-nmt	100	33	27	37
		LMU vs. UHH	100	18	19	59
		PJIIT vs. uedin-nmt	100	68	24	8
		PJIIT vs. UHH	100	28	21	51
		uedin vs. UHH	100	8	29	63
	fr	UHH vs. reference	100	98	2	0
		UHH vs. Hunter	100	67	27	6
		reference vs. Hunter	100	11	23	65
	pl	Hunter vs. PJIIT	100	21	4	7
		Hunter vs. reference	100	84	2	14
		Hunter vs. uedin-nmt	100	48	11	8
		PJIIT vs. reference	100	83	8	9
		PJIIT vs. uedin-nmt	100	62	16	8
		reference vs. uedin-nmt	100	11	14	75
	es	reference vs. UHH	100	1	32	67
	ro	Hunter vs. PJIIT	100	52	38	10
		Hunter vs. reference	100	92	7	1
		Hunter vs. uedin-nmt	100	62	27	4
		PJIIT vs. reference	100	81	16	3
		PJIIT vs. uedin-nmt	100	41	34	24
		reference vs. uedin-nmt	100	6	26	68

Table 11: Results for the manual validation for the NHS datasets.

obtained much higher BLEU scores for en2pt (39 vs. 19), pt2en (43 vs. 21) and es2en (37 vs. 30). However, results for en2es were just a little higher than last year's ones (36 vs. 33).

As the performance of the methods improves on the biomedical domain, it will make sense to introduce additional domain-oriented evaluation measures that provide a document-level assessment focused on the clinical validity of the translations, rather than the grammatical correctness and fluency.

5.2 Best-performing methods

For language for which received submissions from many system, e.g., Cochrane and NHS for en2de, the systems based on neural networks (e.g., uedin-nmt and LMU) performed substantially better than the one based on SMT (e.g., UHH and Hunter). In many runs, the difference in BLEU score was higher than 10 points. The superiority of NMT systems was also observed in the EDP dataset, as implemented in the Kyoto system. However, we also note that a state of the art statistical system relying on rich in-domain and out-of-domain data still performs well (as implemented in the LIMSI strong baseline).

Finally, some teams submitted more than one run but we only observed significant difference on the BLEU scores for some few cases, namely, kyoto (EDP en2fr test set), PJIIT (Cochrane/NHS pl test set), uedin (Cochrane/NHS pl and ro test sets). In the case of the PJIIT systems, the best performing one is an extended version of the base SMT system by including domain adaptation, among other additional features. In the case of the uedin-nmt system, the best performing run relied on advanced techniques, such as +right-to-left reranking.

5.3 Differences across languages

The UHH team developed a MT system based on Moses which was trained on a variety of domain and out-of-the-domain data. However, the same system usually obtained the last ranking position in other languages (e.g., de and fr) for the Cochrane and NHS test sets. Nevertheless, size of the training did not seem to be particularly smaller for German and French, in comparison to Spanish and Portuguese (Duma and Menzel, 2017).

Such differences across languages was also observed for other systems (higher than 10-20 points in the BLEU score). For instance, scores for the uedin-nmt system ranged from 22 (for Czech) to 41 (for Romanian). Interestingly, the scores for the Hunter system ranged from 10 (for Romanian, in contrast to higher scores from uedin-nmt system) to 30 (for French). The Hunter team seems to have used the same approach across all languages and all of these seem to have been trained on a variety of corpora. On the other hand, the uedin-nmt team seems to have used slightly different netwework architectures for the each language (Sennrich et al., 2017).

5.4 Differences across datasets

Given that the methods and corpora seem to be the same for a particular language, differences in BLEU scores across the datasets are probably related to the datasets themselves. Few teams participated in more than one dataset and only one team (UHH) submitted runs for all datasets (for one particular language).

For Spanish, the UHH team obtained considerable differences in BLEU score for Scielo (around 36), NHS (around 41) and Cochrane (around 48). However, their system paper does not give much insight on the reason for such differences (Duma and Menzel, 2017). We can hypothesize that lower scores in the Scielo datasets are due to the fact that the reference translation is not a perfect translation of the source document and sentence alignment was performed automatically.

For French, the Hunter team obtained lower scores in the EDP dataset (around 17) and higher ones in the NHS (almost 23) and Cochrane datasets (around 30). Similarly, the UHH team obtained lower scores for the EDP (around 22) and higher ones for Cochrane and NHS (around 31-32). The reason for these differences is probably the same for the Scielo dataset, this is a automatically acquired test set, whose documents were automatically aligned.

On the other hand, differences also occurred between the Cochrane and NHS datasets, even given that both of them were manually translated. Such differences were usually rather small for most systems (24 vs. 20 for Hunter, 22 vs. 19 for UHH, 25 vs. 21 for PIIJT), for German in the Cochrane and NHS test sets, respectively. However, some cases show larger differences, such as the uedin-nmt system for Romanian (41 vs. 29 for Cochrane and NHS, respectively). In general, results were better for the Cochrane test set and this is probably due to the smaller size of the documents (467 vs. 1044 sentences).

5.5 Differences between manual and automatic evaluations

We checked for differences between the manual and automatic evaluations, i.e., whether a team performed better than another in the manual evaluation but the other way round in the automatic evaluation. We observed small differences for Polish (Cochrane and NHS test sets) between the Hunter and PIIJT teams, but these are probably not significant and both systems have probably similar performance. We observed the same for the UHH and Hunter systems for German (NHS test set). However, we found a more interesting contradiction between Hunter and UHH systems for French in both Cohrane and NHS test sets. UHH obtained higher BLEU scores than Hunter (32-33 vs. 30 and 31-33 vs. 23, for Cochrane and NHS, respectively). However, in the manual evaluation, our expert chose Hunter as being better than UHH in many more sentences (40 vs. 8 and 67 vs. 6, respectively).

5.6 Quality of the automatic translations

We provide an overview of the quality of the translations and the common errors that we identified during the manual validation.

English: Overall, the assessor found the quality of translations into English improved from 2016. Some of the problems observed in the prior year persisted, including inappropriate capitalization of terms (terms were capitalized although they were neither proper nouns nor acronyms) for some translations. Other issues such as incorrect word order as well as untranslated and missing words were observed. Specially in fr2en translations, incorrect word order occurred when the noun-before-adjective grammar in French was erroneously preserved in English; for instance, “douleur oro-faciale” was translated as “pain oro-facial”. Sometimes, however, untranslated words could still be deciphered because the French words were similar to the English equivalents, such as “biomatériaux” vs. “biomaterials”, and “tolérance immunologique” vs. ”immunological tolerance”. As for missing words, translations were severely impacted when entire phrases were omitted, for instance when two consequences of a procedure were reduced to only one.

French: The quality of translations varied from poor to good. The issues that we encountered were similar to last year and included grammatical errors such as incorrect subject/verb or adjective/noun agreement, untranslated passages, incorrect lexical choice due to a lack of word sense disambiguation. One recurring mistake was the translation of the term “female” as “femelle”, which is appropriate for animals instead of “femme”, which is appropriate for humans. This year, the best systems showed an ability to successfully translate some acronyms. However, complex hyphenated terms remained challenging (for example, “38-year-old”, “mid-60s”, “immunoglobulin-like”).

German: Overall, the quality of translations to German ranges from very good to poor. Comparing between the different systems, the translation with the better syntax, grammar and use of technical terms was preferred. When both translations were equally bad their performance was assigned equal. Poor translations are mostly characterized by incorrect syntax and grammar. Syntactic errors are usually due to missing predicates, the usage of two or more predicates in one sentence, and strange word order, especially in long sentences. This often led to confusion or even not understanding the meaning of a sentence. Usual grammar errors included incorrect conjugation of verbs as “wir suchte” instead of “wir suchten” (we searched). In well performing systems syntax and grammar are often correct. Their difference to the reference is often due to not using the most appropriate word. This does not influence the meaning of the sentence. Only as a native speaker one would rather use a different word. All systems seem to have problems with certain technical terms. Usually this occurs when the German translation is very different from the English term. For instance, “to restart a perason’s heart” is often word-by-word translated into “Neustart des Herzen” while in German this procedure is called “Reanimation des Herzens”. The pairwise evaluation of the two best performing teams (LMU and uedin-nmt) indicates, that they often provide similar sentences in terms of grammar and token order.

Portuguese: Only one team (UHH) submitted translation for Portuguese (Scielo dataset). In comparison to submissions from the previous challenge (Bojar et al., 2016), we found the quality of the translations considerably better. As expected, longer sentences usually contained more mistakes and were harder to understand than shorter sentences, usually due to the wrong placement of the commas and conjunctions (e.g., and). For instance, the translation “diâmetro tubular, altura do epitélio seminífero e integridade” was derived from the English version of the reference clause “diâmetro dos túbulos seminíferos, altura e integridade do epitélio seminífero”. However, the same can be also stated for some reference sentences, which could have a higher quality. Regarding more commons mistakes, we observed missing articles, such as “Extratos vegetais” versus “Os extratos das espécies vegetais”. However, we observed less cases of English words which remained in English in comparison to last year, which seems to indicate a better coverage of the biomedical terminology. In some sentences, such cases were observed for terms which were skipped by the translation system, such as “método de manometria de alta resolução” for “high-resolution manometry method for esophageal manometry”. The same mistake was observed for acronyms, e.g., DPS (death of pastures syndrome) instead of SMP (síndrome da morte das pastagens). However, we also found correct translations for acronyms, e.g., SII (síndrome do intenstino irritavel) instead of IBS (irritable bowel syndrome). Finally, we observed other minor mistakes: (a) nominal concordance, e.g., “O fortalecimento muscular progressiva”; (b) wrong word ordering, e.g., “plantadas áreas florestais” instead of “áreas florestais plantadas”; (c) wrong verb tense, e.g., “coeficiente de correlação linear de Pearson spearmans determinado” instead of “determinou”; (d) wrong verb conjugation, e.g, “a umidade relativa, temperatura, velocidade do vento e intensidade de luz foi...”, instead of “foram”; and (e) no contraction when necessary, e.g., “em as” instead of “nas”.

Spanish: Compared to last year’s challenge translations, the quality of the translations into Spanish is significantly better. Despite some small variations, many of the produced translations are valid translations of the original text. There are still cases in which there are mistakes such as with verb tenses “a menudo oír voces”, which should be “a menudo oyen voces”. There are translations with similar meaning but not entirely the same meaning such as “hace aparecer” vs. the reference translation “ocurren”. In some cases, there are some incorrect phrases such as “teléfono NHS informar sobre” vs. the reference translation “llame por teléfono el sistema informativo de NHS en”. Translation systems seem to have better alignment between masculine/feminine and singular/plural articles as compared to last year. In addition, the number of missing words is lower in the Spanish submissions.

Romanian: The quality varied from good translations to clearly underperforming ones. When both translations were good, the one that was grammatically correct was preferred. When one used an awkward language or did not use domain-specific terms such as “traumatism cranian” or “presiune intracraniana”, the other one was preferred. We noticed that these translations can be very dangerous, especially when the form is good (and thus the appearance of quality is high). For instance, in one case, “vasopressor” was translated as “vasodilatatoare”, which is the precise antonym. A frequent mistake was the translation of “trials” as “procese”, which would have been correct for “law suits” but not for clinical trials. Somewhat confusing was translating “norepinephrine” as “noradrenaline”, as they look different but are two names of the same substance. For the bad and very bad translations, errors abounded up to the point that both were equally useless and therefore marked as equal (in the sense of equally bad); this happened quite often. In general, we preferred translations that did not mislead and were still possible to understand despite their many flaws. Among the frequent translation errors, we identified the following: untranslated words, grammatical errors (case, gender), random characters and even Cyrillic (for no apparent reason) and context which were frequently not considered (e.g. “shots” translated to “gloante” and “impuscaturi”, those words having to do with weapons not with syringes). Other strange errors included unrelated words from other fields, especially “subcontractantul copolimerului” or “transductoare AFC”.

6 Conclusions

We presented the results of the second edition of the Biomedical task in the Conference for Machine Translation. The shared task addressed a total of ten languages and received submission from seven teams. In comparison to last year, we observed an increase on the performance of the systems (in terms of higher BLEU scores) but also an improvement on the quality of the translations (as observed during manual validation), The methods behind the systems included both statistical and neural machine translation techniques, but also many advanced features to boost the performance, such as domain adaptation.

Despite the comprehensive evaluation that we show here, there is still room for improvement in our methodology. We did not perform statistical tests when ranking the various systems and runs in both manual and automatic evaluations. Further, each combination of two translation or one translation and reference was evaluated by on single expert, given the high number of submission and difficulty on finding available experts. On the other hand, most results obtained through manual validation were consistent with the ones from automatic validation.

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